Ensemble downscaling of winter seasonal forecasts

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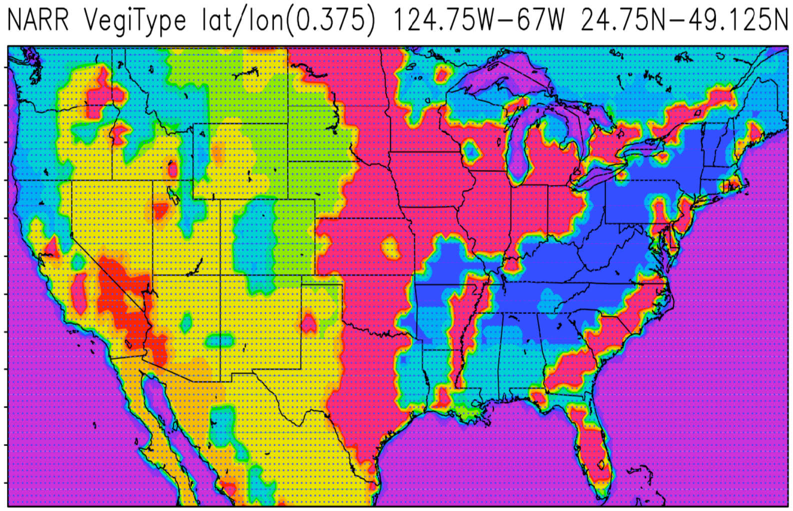
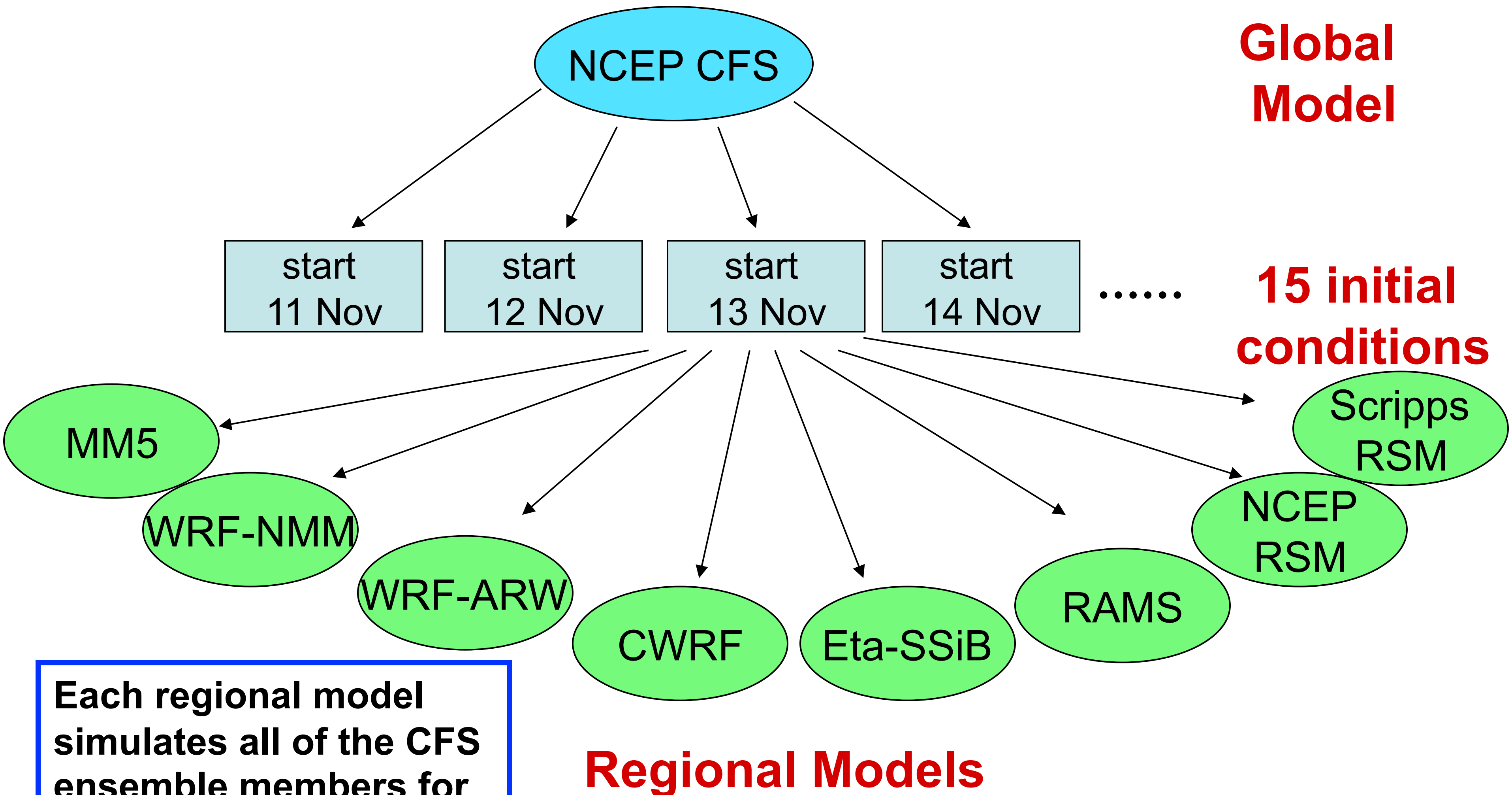
Multi-RCM Ensemble Downscaling of multi-GCM Seasonal Forecasts (MRED)

- Test usefulness of limited-area models to downscale **winter seasonal forecasts** from global models.
- Downscale 23 years of winter (December-April) reforecasts from NOAA CFS global seasonal forecast model (T62L64, ~1.9° lat/lon).
- Domain is the coterminous U.S. at grid spacing 32 km.
- Downscale each member of a 15 member CFS ensemble for each winter 1982-2004.



MRED Ensemble

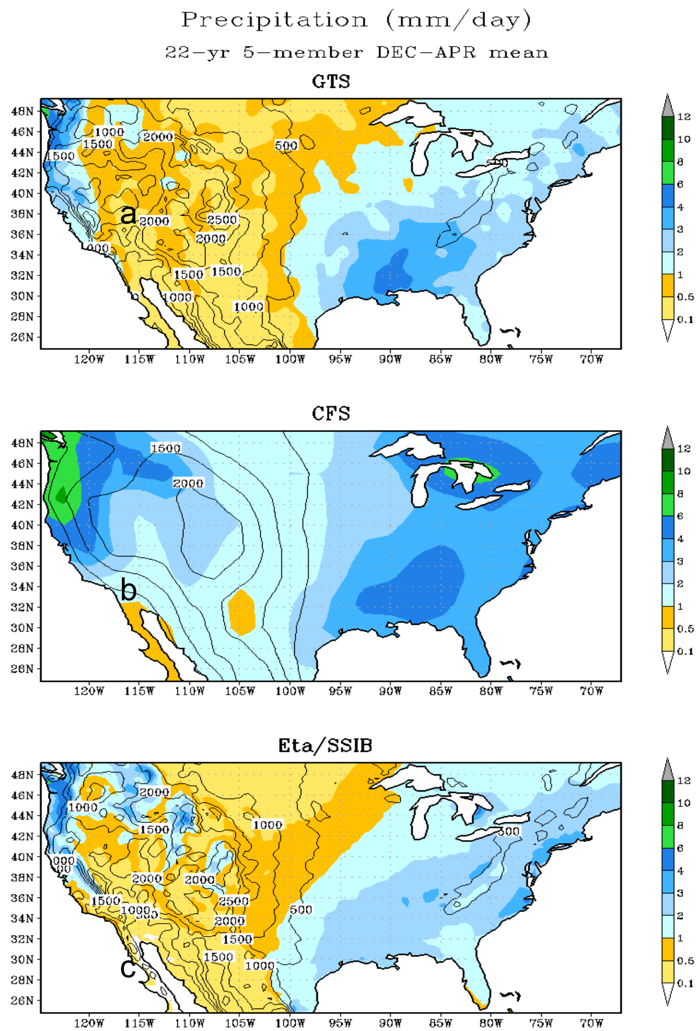


Each regional model simulates all of the CFS ensemble members for each winter.

Preliminary results from MRED

- Each group is analyzing their own results. A few examples are shown here.
- Preliminary results also are shown for the simulations as a multi-model ensemble.

Refinement of spatial detail for precipitation over all winters (Dec-April, 1982-2004) in ETA/SSiB



Statistics comparison

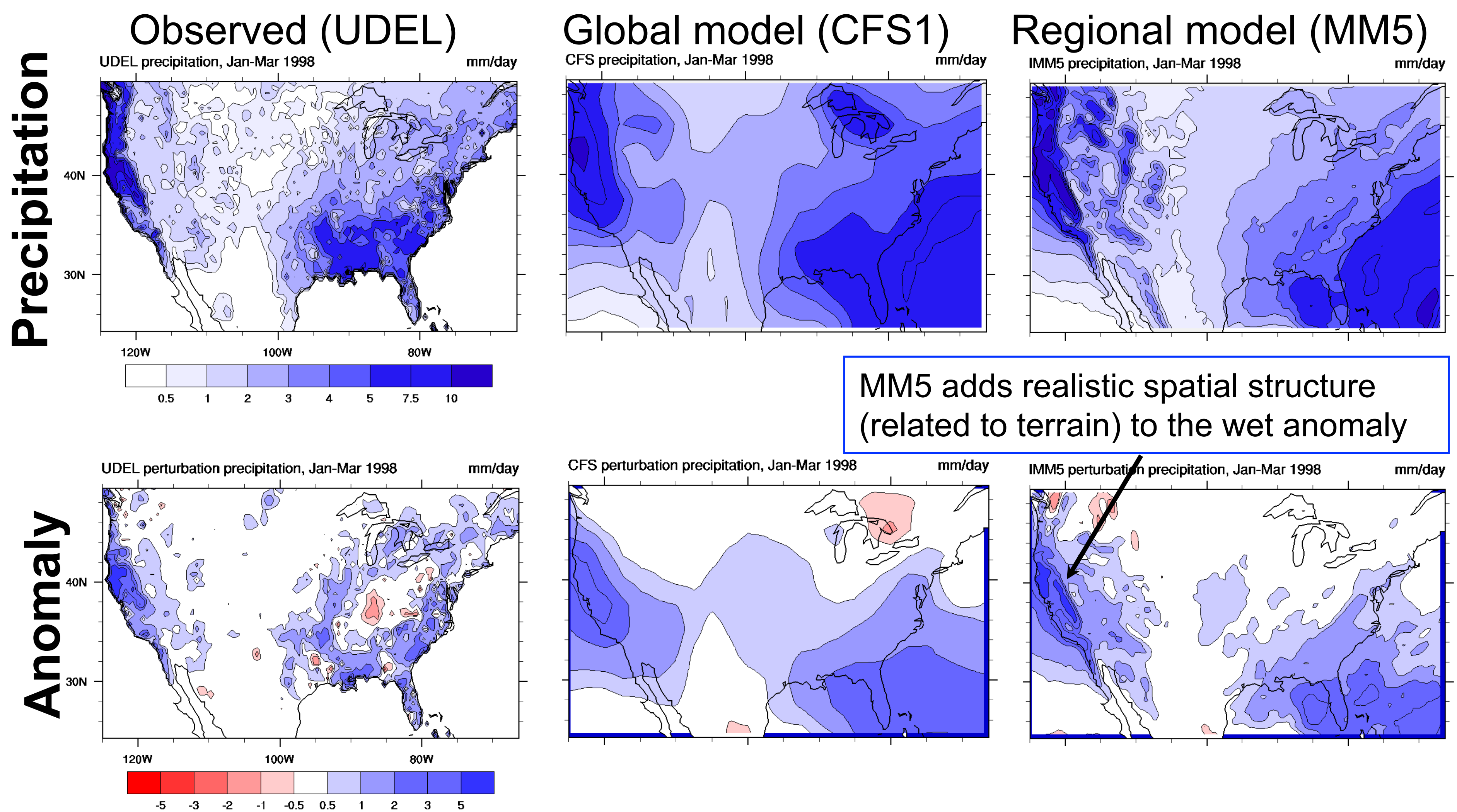
	Mean	Bias	RMSE	SCorr
GTS	1.34			
CFS	2.86	1.52	1.79	0.70
ETA/SSiB	1.33	-0.1	0.60	0.82

Eta/SSiB reduces both the mean bias and the RMSE compared to CFS. Spatial correlation also is improved.

Dec-Apr 1982-2004 average precipitation for a) observation, b) CFS ensemble mean, and c) ETA/SSiB ensemble mean (mm day^{-1}) and topography (m)

Refinement of spatial detail in MM5 for January-March 1998 precipitation (strong El Niño)

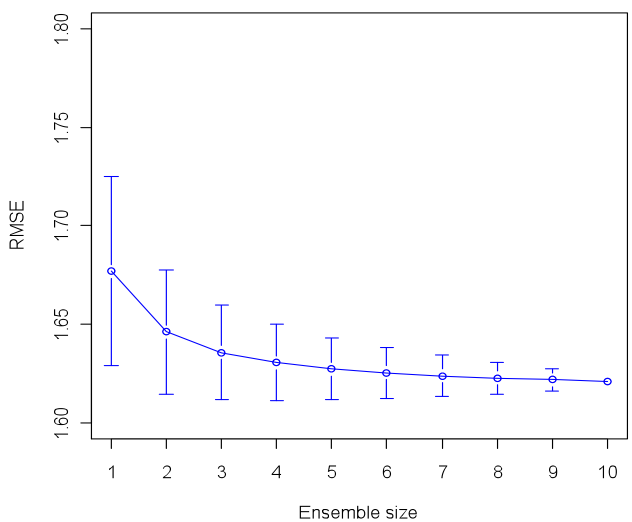
Average over 15 ensemble members



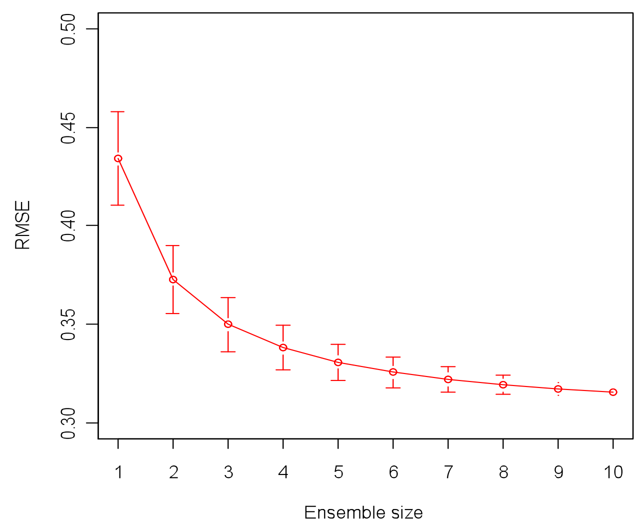
Downscaled precipitation in Eta/SSiB has smaller RMSE and benefits more from ensemble size compared to CFS

RMSE of temporal variation for precipitation (U.S. average)

CFS



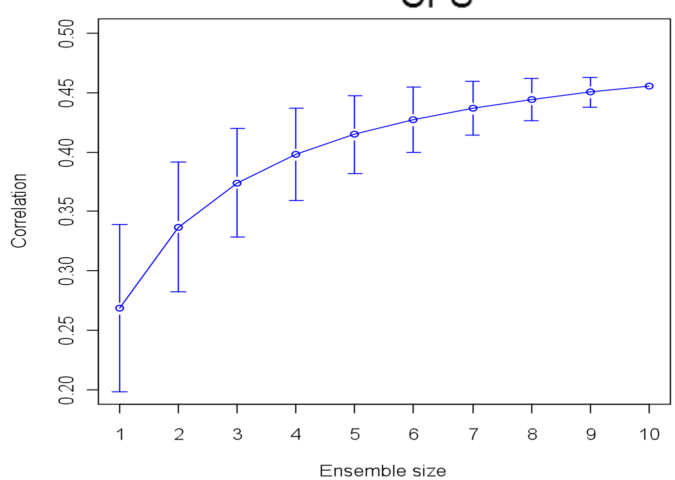
ETA-UCLA



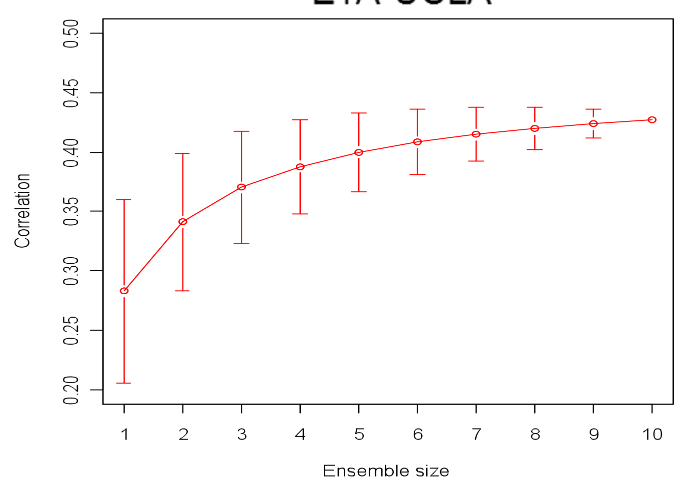
Results are shown for one model (Eta/SSiB)

Temporal correlation for precipitation (U.S. average)

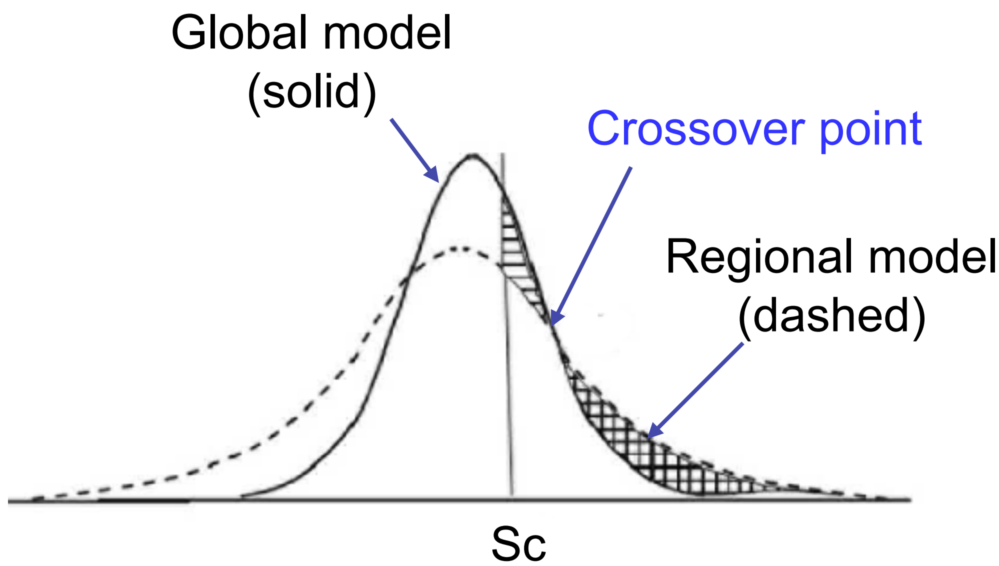
CFS



ETA-UCLA



A new metric for summarizing the "value added" by downscaling



Consider differences in statistical distribution of skill, not just changes of mean skill.

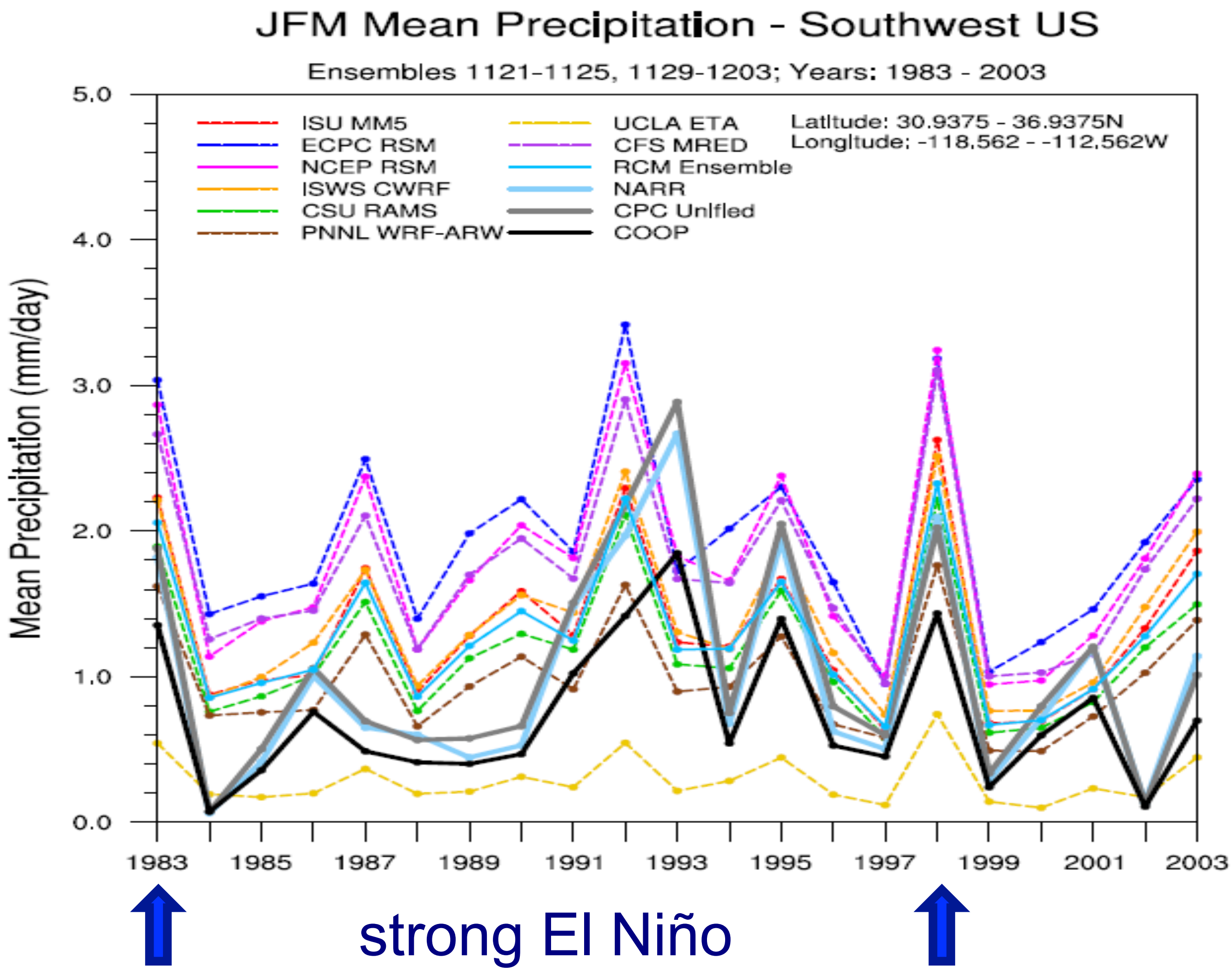
Look at the region above a critical skill level (Sc) representing minimum useful skill.

Added Value Index (AVI) is the area between the curves beyond the crossover point where regional model skill begins to exceed global model skill (if the crossover point exists).

Interpretation: Regional model skill is higher than global model over AVI % of the domain for the corresponding skill range.

After Kanamitsu and DeHaan, 2011, J. Geophys. Res., doi: 10.1029/2011JD015597

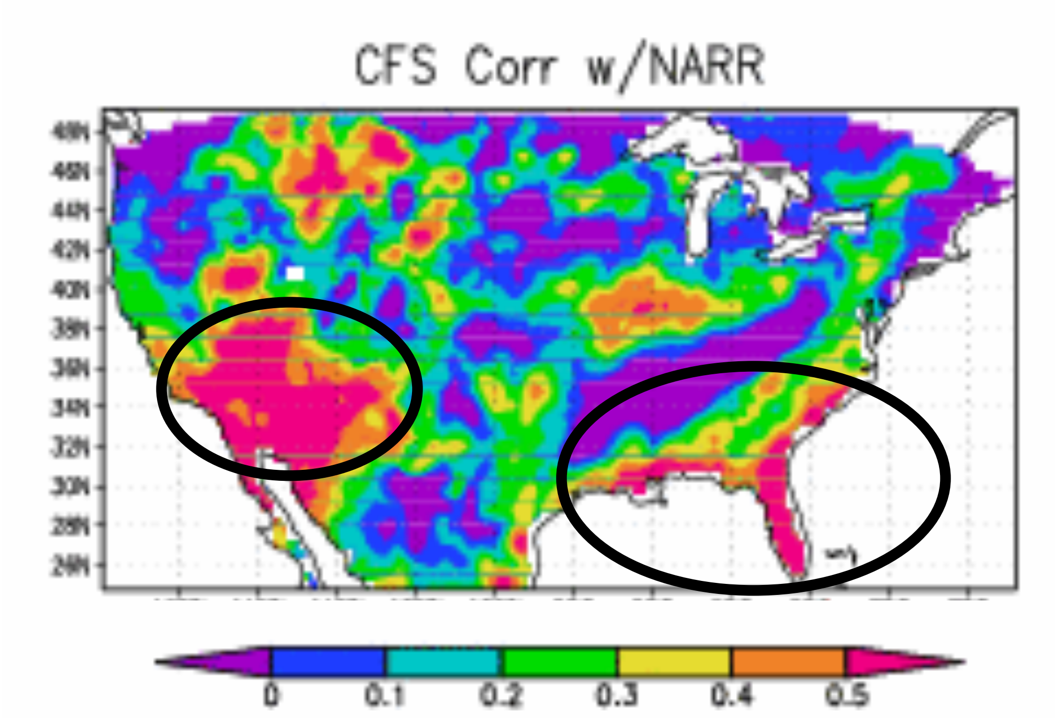
Individual models mostly track the CFS. For a given model and region, each model usually has a consistent offset from the CFS



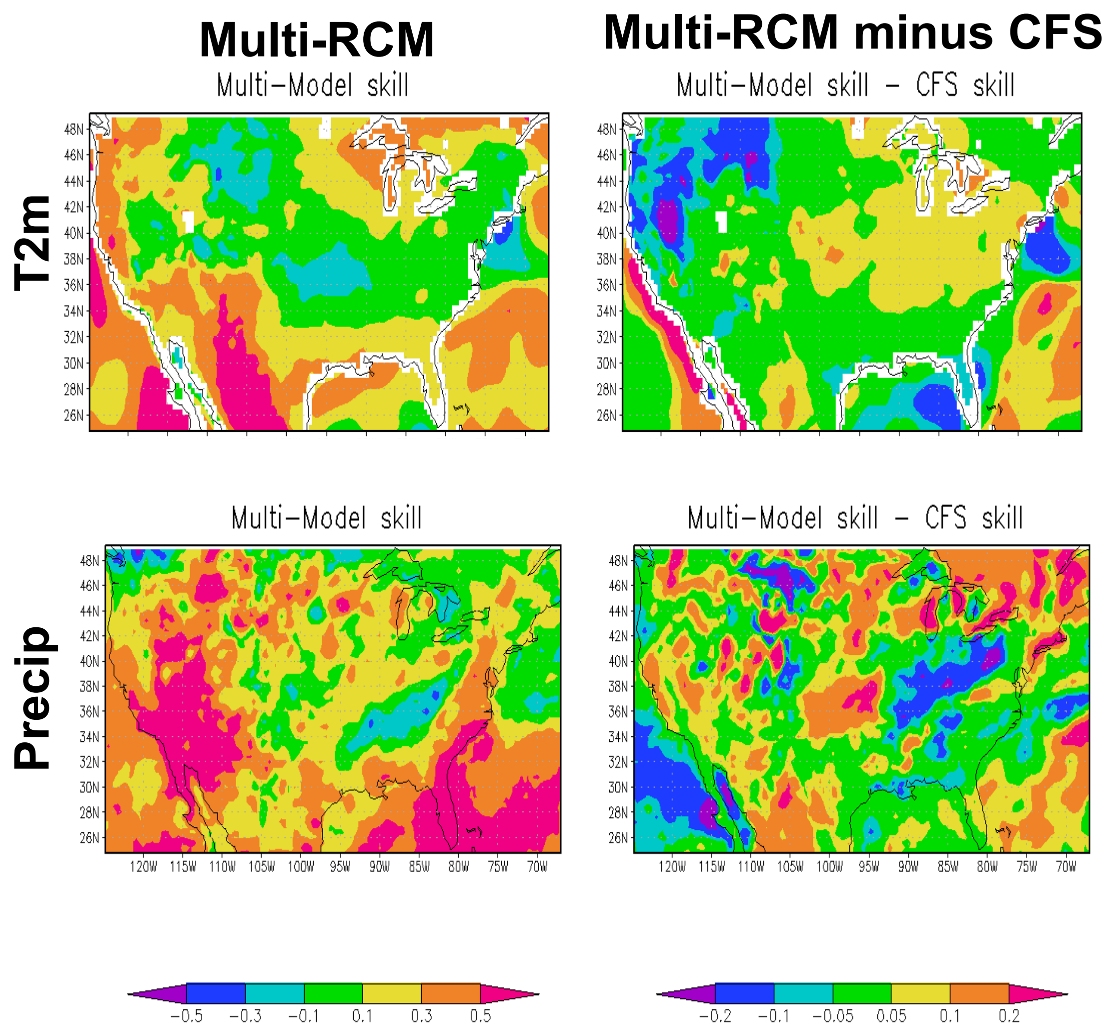
strong El Niño

Preliminary evaluations of multi-RCM skill

- Regional model skill ultimately depends on skill of the driving global model.
- CFS has its highest precipitation skill in the southwestern and southeastern U.S. Both of these regions have a strong ENSO signal.



Comparison of temporal correlation for CFS and the multi-model ensemble



T2m

Improvement for the multi-RCM ensemble occurs only in a few areas. The region of skill increase in much of the northeast still has negligible skill even though the regional models improve on the global model.

Precipitation

The multi-RCM ensemble has higher precipitation skill than the CFS over much of the U.S. The pattern of skill improvement is complex and sometimes is tied to terrain features.

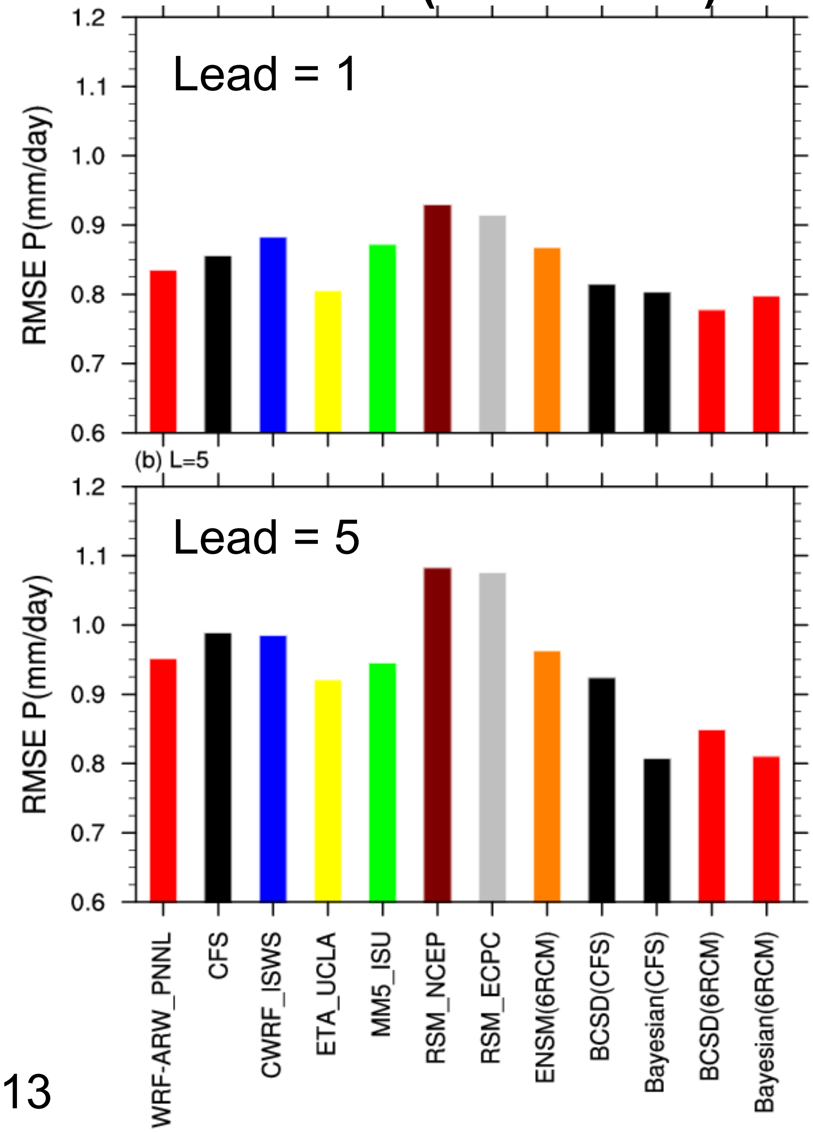
Application of statistical methods to downscaled results

- Apply two different statistical downscaling methods to the driving CFS and 6 RCMs:
  - BCSD (Bias Correction and Spatial Disaggregation): Correct the PDF based on long-term observations (Wood et al. 2004)
  - Bayesian merging: Correct the PDF based on long-term observations and skill of hindcast (Luo et al. 2007)

Work in progress by Jinho Yoon, Jimmy Correia, and Ruby Leung, PNNL

Precipitation

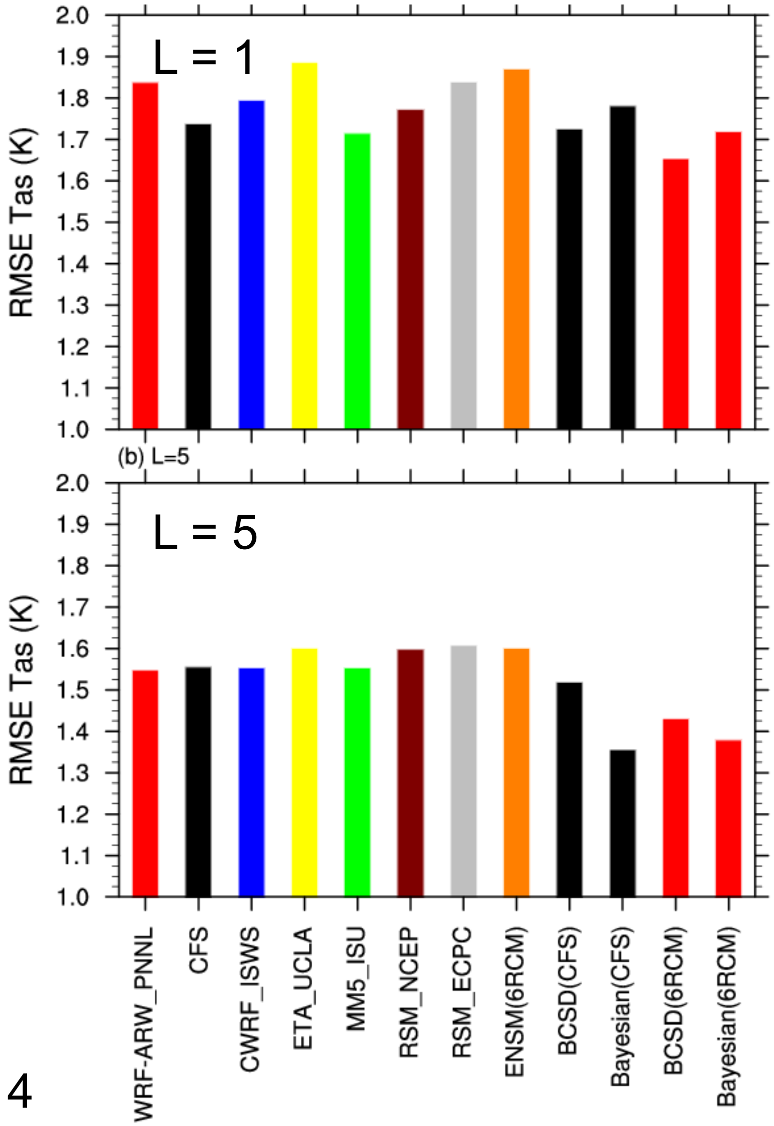
RMSE for precipitation, averaged over the US (1982 – 2003)



- RMSE of P anomaly (= P – P_{mean}) computed for CFS and for each regional model, as well as for statistical methods applied to the model output
- For one-month lead, BCSD for all 6 RCMs (ensemble mean) has the smallest RMSE.
- Bayesian performs well at longer leads, but not much difference between statistical methods.

Surface Temperature

RMSE for temperature, averaged over the US (1982 – 2003)



- For one month lead (L=1), BCSD of all 6 RCMs again has the smallest RMSE.
- At longer leads there is not much difference between statistical methods (slight advantage for Bayesian method).
- Analysis of both P and T shows that RCMs combined with statistical methods produce the highest skill, especially for shorter leads.
- There is no "best" or "worst" single RCM across all variables: Models with lowest RMSE for precipitation do not necessarily have lowest RMSE for temperature.

Some preliminary findings

- Regional model results show true **downscaling**: Results follow the global model but with more spatial detail.
- Added value (skill) from downscaling varies with region and variable: for example, winter downscaling shows more improvement for precipitation than for temperature.
- Both the skill of downscaled results and **improvement** over the global model tend to be greater for variables, events and locations where the global model already is skillful:
  - As with the global model, best skill is for strong El Niño.
- Statistical post-processing helps extract value from downscaled forecasts.
- Skill of downscaled results ultimately is tied to the skill of the global model (GIGO). **Improved global model forecasts should lead to improved downscaling.**

Where do we go from here?

- Test the MRED approach for summer.
- Dependence of downscaled results on the global model: apply multi-model seasonal downscaling to multi-model global forecasts.
  - apply lessons learned from NARCCAP and other multi-GCM x multi-RCM projects
- **Hypothesis:** Downscaling from multiple GCMs will produce improved statistics compared with same size RCM ensemble from a single GCM.